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WITNESS my hand this
Sixth day of February 2003

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PROVISIONAL SPECIFICATION

Invention Title: "PERFORMANCE MONITORING SYSTEM AND METHOD"

The invention is described in the following statement:

PERFORMANCE MONITORING SYSTEM AND METHOD

The invention relates to a performance monitoring system and method. In particular, although not exclusively, the invention relates to a system and method for monitoring the performance of equipment operators, particularly operators of draglines and shovels employed in mining and excavation applications or the like.

BACKGROUND TO THE INVENTION

In many fields of manufacturing and industry, it is desirable or necessary to monitor the performance of equipment operators in addition to the equipment itself. This may be for managerial purposes to ensure that operators are complying with a minimum required standard of performance and to help identify where improvements in performance may be achieved. Monitoring performance may also be desired by an operator to provide the operator with an indication of their own performance in comparison with other operators and to demonstrate their level of competence to management.

One field in which performance monitoring is required is the operation of draglines and shovels and the like as used in large-scale mining and excavation applications. For commercial purposes, it is important that an operator is operating a piece of machinery to the best of the operator's and the machine's capabilities.

There are however many factors that need to be measured and considered to enable fair and useful comparisons to be made between different operators, between different machines, between present and previous performances and between different operating conditions.

It is therefore desirable to provide a system and/or method capable of achieving this objective. Furthermore, it is desirable that performance-monitoring information is promptly available to inform management and operators alike of current performance.

DISCLOSURE OF THE INVENTION

According to one aspect, although it need not be the only or indeed the broadest aspect, the invention resides in a method for monitoring performance of at least one machine operator, the method including the steps of:

measuring at least one machine parameter during operation of the machine by the operator;

generating at least one performance indicator distribution from measurements of the at least one machine parameter; and,

calculating at least one performance indicator from the at least one performance indicator distribution.

The method may further include the step of providing feedback to the operator by displaying the at least one performance indicator in substantially real-time to the operator. Alternatively, the at least one performance indicator may be displayed to the operator once the machine has completed an operation cycle.

Suitably, the at least one machine parameter may be a dependent machine parameter. Alternatively, the at least one machine parameter may be the sole parameter represented by a particular performance indicator.

The method may further include the step of segmenting at least one of the dependent machine parameters into segments, the range of each segment constituting a segmentation resolution.

Suitably, the step of segmenting at least one of the dependent machine parameters includes specifying a magnitude of the range for each segment of each dependent machine parameter requiring segmentation.

Suitably, at least one dependent machine parameter may not require segmentation.

Suitably, the step of generating the at least one performance indicator distribution may comprise using a mixture of one or more distributions to model the performance indicator distribution. The number of mixtures may be set dynamically.

Suitably, the at least one performance indicator distribution may be generated using an algorithm. The algorithm may be an LBG algorithm. Alternatively, the at least one performance indicator distribution may be generated using a linear ranking model (LRM).

Suitably, two or more performance indicators may be combined to yield an overall performance rating. One or more of the performance indicators may be positively or negatively weighted with respect to the other performance indicator(s).

According to another aspect, the invention resides in a system for monitoring performance of a machine operator, the system comprising:

at least one measuring device for measuring at least one machine parameter during operation of the machine by the operator;

a server for generating at least one performance indicator distribution from measurements of the at least one machine parameter; and,

a calculator for calculating at least one performance indicator from the at least one performance indicator distribution.

Preferably, the server is remote from the machine.

Suitably, the server comprises storage means, calculation means and communication means.

Suitably, the calculator is located in, on or about the machine.

Preferably, the calculator is connected to communication means for transmitting and receiving data to and from the server.

Preferably, the system further comprises at least one display device for displaying the at least one performance indicator in substantially real-time to the operator. Alternatively, the at least one performance indicator may be displayed to the operator once the machine has completed an operation cycle. The at least one display device may be situated in, on or about the machine and/or remote from the machine.

Suitably, the communication means comprises a transmitter and a receiver.

Further aspects of the invention will become apparent from the following

description.

BRIEF DESCRIPTION OF THE DRAWINGS

To assist in understanding the invention and to enable a person skilled in the relevant art to put the invention into practical effect preferred embodiments will be described by way of example only and with reference to the accompanying drawings, wherein:

FIG 1 shows a distribution of data representing the production KPI;

FIG 2 is a schematic plan view of a machine showing the segmentation resolution for the swing angle variable;

FIG 3 shows a distribution of Fill Production KPI data;

FIG 4 shows dragline data for the variables start fill reach versus start fill height;

FIG 5 shows calculation of a KPI for the right side of the distribution;

FIG 6 is a schematic representation of the IMS structure;

FIG 7 shows a display of KPIs showing current real-time performance and a comparison with performance for a previous cycle;

FIG 8 shows a display of KPIs showing current real-time performance;

FIG 9 shows an alternative display of KPIs showing both current real-time performance and performance for a previous cycle;

FIG 10 shows an Operator Performance Trend Report; and

FIG 11 shows an Operator Ranking Report.

DETAILED DESCRIPTION OF THE INVENTION

The present invention monitors one or more parameters or variables of a machine to provide an accurate indication of how well an operator is performing, for example, in comparison with other operators for the same machine and/or in comparison with previous performances of the same operator.

A machine parameter may itself be referred to as a key performance indicator (KPI). Alternatively, a KPI may be dependent on one or more machine

parameters. The KPIs may be represented and displayed as a percentage or a score, such as points scored out of 10, that describes how well the operator is performing for a given parameter/KPI. A high percentage value, such as >90% for example, shows that the operator is performing extremely well. A mid-range value for a KPI, such as 50% for example, shows that the operator's performance is about average and less than this percentage, their performance is below average for that KPI.

Each KPI parameter is related to the performance of an operator for one or more given machine parameters such as fill time, cycle time, dig rate, and/or other parameter(s). KPIs are a measure of how the operator is performing for the particular parameter(s) related to that KPI compared to the other operators. The performance of, or rating for, a particular operator is calculated using, in part, previous data recorded for the machine and provides an indication of whether or not the operator is improving. The process for measuring the parameters and achieving the KPIs is described in detail hereinafter.

The parameter data is acquired using conventional measuring equipment such as sensors, timing means and the like and the particular equipment required to acquire the data would be familiar to a person of ordinary skill in the relevant art.

Different comparisons between the data are also possible. The current operator of a machine can be compared to all the other operators of the same machine or to the operator's previous performance(s). This shows how well they perform against others and shows them whether they are improving respectively.

One important consideration of the present invention is filtering the data from all the machines that may be present in, for example, a mine site or other situation. Various factors that may affect KPI parameters are as follows:

Machine: Each machine possesses different operating characteristics and therefore the data from one machine will not reflect the

performance of operating another machine.

Dig Mode: Different dig modes are possible with a single machine and these may differ between different machines, which is significant. In the present invention operators can enter a particular dig mode corresponding to the mode of operation of the machine. The selected dig mode must be correct otherwise the KPIs may be mis-represented and provide misleading results.

Operator: Operators can compare their performance against their own previous performances to verify whether they are improving. Operators can also compare their performances against those of other operators.

Location: Different locations in the mine will have different digging conditions even though the digging mode may be the same. This may be represented by the specific gravity (s.g.) or by an index that describes the current digging difficulty, known as the dig index.

Bucket: Some KPIs will be affected by the type of bucket being used on the dragline. For example, different size buckets, which are usually pre-selected on the basis of the application, may produce different dig rates. For comparison purposes, an operator should not be disadvantaged when using a smaller bucket.

Bucket Rigging: If this factor changes and the bucket does not, the KPI results may be affected.

Weather: The weather can change the digging conditions and therefore affect the performance attained by the operator.

Some of the above parameters are readily filtered from the data, such as machine, dig mode, operator, bucket and possibly location. The more the data is divided however, the more data needs to be processed, stored and sent to the module (shown in FIG 6), to implement KPIs. The location parameter could possibly be omitted as this may be reflected in the bucket type being used. Weather and bucket rigging are more difficult to filter. Therefore, the parameter filters of machine, dig mode and bucket remain.

These parameter filters may be combined with the operator parameter filter.

If the data of all operators are to be compared, the operator filter is omitted. When filtering by operator, the number of operators multiplies the amount of data for the mine comparison. For example, if there are 1000 bytes of KPI data to download to the module for the mine data and there are 100 operators, then this equates to a total of 101,000 bytes of KPI data to download, which represents 100 data sets for 100 operators plus one data set for the all operator comparison.

This large data problem is one of the problems addressed by the present invention, which enables the present invention to provide substantially real-time monitoring of operators' performance.

The large data problem can be solved in a number of ways. One option is to only download KPI data for the operators that exist in the recorded data in the database. Alternatively, only KPI data for operators that have ever logged onto a particular machine, which is stored in an operator profile, may be downloaded. For any new operator who logs on, the data is requested and downloaded. If the data does not exist in the database, then the display can show that there is no KPI data for that operator. Another alternative is to just download the KPI data for the operator that just logged on.

Even with the data filtering described above, a single value such as fill time, cannot be compared to other fill times unless one or more dependencies are introduced. Some KPIs, such as the Machine Reliability KPI, do not require a dependent parameter, but many do, such as the Swing Production KPI. A dependent parameter adds another level of filtering to the data that is specific to the parameter being rated.

A simple example is the Swing Production KPI. The time taken to swing a dragline, for example, is directly related to the angle the dragline swings (Swing Angle) and the vertical distance the bucket travels from the end of a fill to the top of a dump. These dependencies are included in the KPI calculation by segmenting each of the dependent parameters into ranges.

The range of the segment is called the segmentation resolution. The swing angle in this example could be divided into 10-degree increments over, for example, 360 degrees. If the vertical travel distance is ignored in this example, this would provide 36 data segments.

To calculate the KPI, the data recorded from that machine is sorted, for example, by dig mode, for each of the segments. For the data associated with each segment, a KPI distribution is calculated. Therefore, for the Swing Production KPI example, the swing times for each swing angle segment are extracted and a distribution is calculated for each. Thus, 36 distributions would be calculated in total. The actual swing time and swing angle are measured onboard the machine. The distribution associated with the swing angle segment being measured is then selected to calculate the KPI.

Introducing more dependent variables creates the problem of producing more data segments, which in turn means more distributions and more data. In the example above, if the vertical distance was included and divided into, for example, 10 metre segments from 0 to +70 metres (7 segments), there would be 252 (36 x 7) distributions to calculate and download to the machine just for the Swing Production KPI.

This can be reduced by carefully designing the segmentation of the dependent parameters. One way is to include the extremities in the segmentation, which should allow only segmentation of the areas that are common. In the above example, the swing angle could be re-segmented such that one segment contains swing angles less than, for example, 30 degrees and another segment contains swing angles greater than, for example, 200 degrees whilst maintaining the 10-degree segments between 30 degrees and 200 degrees. This re-segmentation results in 19 segments for the swing angle parameter.

The vertical height dependency could be reduced to 2 segments by identifying the height at which the swing velocity is reduced (i.e., for hoist dependent swings). Less than this height is one segment and above this height is another. This reduces the total number of segments to 38

segments.

As described in the foregoing, a distribution exists for each segment of the KPI dependent on some other parameter. Finding a distribution that describes the KPI data is not trivial. Even though the sampled data looks Gaussian in nature, the graphs are skewed and comprise some data at the extremities.

FIG 1 shows some data taken for the KPI representing production. All the other KPIs showed a similar distribution. FIG 1 shows a positive skew in the data and some data to the right of the graph. A simple Gaussian would model most of this data quite adequately. However, it cannot be judged how the data will skew or how the distribution will change once the KPI information is available to the operator. It is likely that the distribution will become more positively skewed and less Gaussian like.

One solution to this problem is to model the data with a multi-modal or multi-variant Gaussian mixture in which a mixture of different Gaussian distributions are used to model each KPI distribution. This has the advantage that the number of mixtures can be changed depending on the data. If the data is very Gaussian-like, then a single mixture comprising a simple Gaussian distribution may be used. If the data is very obscure, then a plurality of mixtures can be used to describe the distribution.

The number of mixtures depends on the data that is being modeled and may be set dynamically. With sufficient data, an algorithm could be employed to determine the maximum number of mixtures required to represent the KPI distribution. If there is little data, for example less than a selectable threshold of 10 samples, then modeling may be carried out using a single mixture. If the algorithm does not converge with the maximum number of mixtures, the highest number of mixtures that cause the algorithm to converge can be used.

One algorithm that could be used to generate the KPI distributions from the data is an algorithm known to persons skilled in the relevant art and is called the Linde-Buzo-Gray (LBG) algorithm. The LBG algorithm is an

iterative algorithm that splits data into a number of clusters. The algorithm is designed for vectors, but in the present invention, single dimension vectors (single values) are used, thus simplifying the algorithm.

The detail of the LBG algorithm will now be described. $X_m = \{x_1, x_2, ..., x_M\}$ is the training data set consisting of M data samples. $C_n = \{c_1, c_2, ..., c_N\}$ are the centroids calculated for N clusters. ε is the iteration conversion coefficient, which is usually fixed to a small value greater than zero, such as 0.01.

The steps for generating the KPI distributions are as follows:

1. N = 1 and given X, calculate the initial centroid C_1 by calculating the mean:

$$C_1 = \frac{1}{M}\sum_{m=1}^{M} x_m$$

2. Calculate the initial distortion of the data for the initial centroid:

$$D_{avg}^{0} = \frac{1}{M}\sum_{m=1}^{M} |x_m - c_1|^2$$

3. Set iteration index $I = 0$.

4. Find the cluster p with the maximum distortion.

5. Increment the number of clusters: N = N + 1

6. Split cluster p into 2:

$$c_p = (1+\varepsilon)c_p$$

$$c_N = (1-\varepsilon)c_p$$

7. For all $1 \le m \le M$ in the data set X, record the nearest centroid $c_{n^*}^{(i)}$ where n^* is the index of the centroid:

$$Q(x_m) = c_{n^*}^{(i)},$$

and the total number of values assigned to each centroid T_n.

8. Calculate the new centroids:

$$C_n^{(i+1)} = \frac{\sum_{Q(x_m)=c_n^{(i)}} x_m}{\sum_{Q(x_m)=c_n^{(i)}} 1}$$

$$\text{or } C_n^{(i+1)} = \frac{\sum_{Q(x_m)=c_n^{(i)}} x_m}{T_n}$$

9. $i = i + 1$.

10. Calculate the average of the minimum distortion between the data sample and its closest centroid:

$$D_{avg}^{i} = \frac{1}{M}\sum_{m=1}^{M}\left|x_m - Q(x_m)\right|^2$$

11. If $\left(D_{avg}^{(i-1)} - D_{avg}^{(i)}\right)/ D_{avg}^{(i-1)} > \varepsilon$, then go back to step 7.

12. Save the temporary calculation centroids in a secure location.

13. If the number of desired clusters has not been reached, then go back to Step 4.

The algorithm starts by treating the whole of the data as one cluster. It then divides the cluster into two and iteratively assigns data to each of the clusters until the centroids of the clusters do not move appreciably. Once the iterations converge, the cluster with the greatest spread (accumulative distance between data and centroid) is split and the iterative calculations are repeated. The algorithm continues until the required number of clusters has been reached. The result is data divided into clusters with centroids. The data for each cluster is then used to calculate a mean and standard deviation for that cluster, i.e. a distribution. The weight of each cluster is calculated as the number of data samples in the cluster compared to the total number of data samples. This weight is known as the mixture coefficient.

In order to calculate the KPI from the distributions, the following formula for a multi-variant Gaussian distribution is employed:

$$p(x) = \sum C_n \mathrm{N}(x, \mu, \sigma)$$

where *p(x)* is the probability, C_n is the mixture coefficient and $N(x,\mu,\sigma)$ is represented by the following formula:

$$\mathrm{N}(x, \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

which is a standard Gaussian distribution with mean μ and standard deviation σ.

Another solution to the problem of modeling the data to generate the KPI distributions is to use a Linear Ranking Model (LRM). Instead of modeling the distribution of each of the segments for each KPI, the LRM models the distribution in such a way that only the minimum and maximum boundaries need to be calculated. All values between these limits are then ranked according to their position between the minimum and maximum. This method has the advantage that it is distribution independent.

One problem with the LRM is that is does not handle outlying data very well. For example, with reference to the Fill Production data shown in FIG 3, there is an amount of data to the right of the graph (caused possibly by abnormal cycles). The minimum and maximum values are 0.33 and 34 (units =mass per time interval) respectively for this example. This means that the majority of the operators would obtain a low score and very few would obtain a high one since the majority of Fill Production values would occur in the lower half of the range.

A solution to this problem is to filter off the erroneous data. This can be achieved by removing data that is more than 3 standard deviations from the mean (keep 99% of the data for true Gaussian curve). The new minimum and maximum are −0.70 and 17.6. The negative minimum would be set to zero and any values greater than the maximum are then deemed 100%.

Another consideration is that most of the scores obtained by the operator will be around the average because we are modeling a Gaussian-like distribution using a linear model. That is, as most of the data is centred on the mean, the majority of the scores will be around the mean. There is also the consideration that the scores are represented as a percentage, which no longer has a physical meaning. Instead, the operator will receive a score out of 10.

The solution for the threshold problem is to calculate the thresholds in the office. The mean sets the lower threshold so that if the operator obtains a score below this then the operator is below average. For the upper threshold, the threshold for the top 10% of operators can be found. The data

used to calculate these thresholds is all the data for each KPI without segmentation. The threshold is then the average score of the thresholds over the KPIs. This means that we have a set threshold for all KPIs and one that does not vary from cycle to cycle.

The score for the KPI using the Linear Ranking Model is the ratio between the value and the difference of the minimum and maximum. This value is then multiplied by 10 to produce the KPI score. The following equation shows the calculations required:

$$score = 10 \times \frac{value - \text{minimum}}{\text{maximum} - \text{minimum}}$$

TABLE 1 below shows the advantages and disadvantages of the LRM and LBG methods for generating the distributions.

TABLE 1

Issue	Gaussian Model	Linear Ranking Model
Normal Gaussian curve	Models this well.	Will have a small problem in that most of the values concentrate around the mean so it is less likely for an operator to achieve above 80% and less than 20%. This can be addressed by lowering the thresholds. Conceivably, these thresholds could be set dynamically in the office.
Skewed Data (After using KPIs for a while)	May have a problem if a lot of the operators show an increase in performance. The worst of the best will actually be penalised by only receiving an average score.	Will handle this well.
Low amount of data	Will only model the data that it is given.	Same problem as the Gaussian Model but can be fixed by applying manual limits.

Spurious data	Handles this automatically.	Filtering will need to be applied to remove the outlying data. Taking the mean and removing any data more than 3 standard deviations from the mean will help this.
Maths	Requires a clustering algorithm to model the data.	Simple minimum and maximum after applying a simple Gaussian curve to filtered data. Upper and lower constraints can also be applied.
Other	Once implemented, we cannot change the way the data is represented easily.	We can change the way the limits are calculated with no change to the on-board system.

The parameters represented by KPIs and their dependent parameters are:

1. **Swing Production = Load Weight / Swing Time**
   Swing Angle
   Hoist Dependent Swings

2. **Fill Production = Load Weight / (Fill + Spot Times)**
   Start Fill Reach
   Start Fill Height

3. **Return Time**
   Swing Angle

4. **Production Performance**
   This is a weighted sum of the 3 KPIs above.

5. **Machine Reliability**

Hence, there are 5 KPIs and 4 different dependent parameters. The Hoist Dependent Swings parameter does not require segmentation at all, as it is a Boolean. That leaves only 3 dependent parameters for which segmentation needs to be described.

However, it will be appreciated that the present invention is not limited to these numbers of KPIs and different dependent parameters. It is envisaged that other parameters and KPIs and combinations thereof may be utilized in future, depending particularly on, for example, the particular

application.

In accordance with the present invention, a segmentation resolution is set for each dependent parameter in the database structure, except for the Hoist Dependent Swings parameter as previously explained. The segmentation resolution specifies the relevant variable(s), such as distance, angle, and the like, for a single segment. For example, if the segmentation resolution for Swing Angle were 15 degrees, then data would be extracted for each 15-degree segment, as indicated in FIG 2. A weighted sum of the first 3 KPIs may then be calculated to obtain an overall performance rating.

Segmentation is performed from a single known point (such as the origin in the case of the Start Fill Reach and Height). The data is then segmented from this point based on the segmentation resolution as explained above. Segments continue until the maximum or minimum limit is reached.

For example, FIG 4 shows fill time data for different Fill Reaches and Heights. The segments would be divided such that they start at 0 cm and extend out to the 10,000 cm extremity in the Fill Reach case. For the Fill Height, the segments would extend up to the 1,000 cm extremity and down as far as the -3,500 cm extremity.

The reason to perform the segmentation in this way is so that the distributions represent a fixed set of conditions even after a period of time. This way, data that was logged, for example, a month ago can be compared with the current distributions.

Another setting for the KPIs related to the segmentation is the calculation of a probability from the distribution. If a better performance is achieved by a lower KPI value, the right side of the distribution needs to be calculated to obtain the KPI, as shown in FIG 5. The Return Time KPI is an example of such a KPI. The left side of the distribution is calculated when a KPI value is required to be higher to achieve better performance. The Swing Production and Fill Production KPIs are examples of such a KPI.

FIG 6 shows the structure of the Integrated Mining Systems (IMS) system. A Series 3 Computer Module and associated Display Module are

located in each machine on site. The IMS server may also be located on site, for example in the site office, or it may be located at some other remote location providing communication within the Telemetry constraints is possible.

The Database also needs to store the KPI Distributions that are generated from the cycle data. A number of distributions are stored in the Database. The first set of Distributions model the data for that machine for all operators. A set of Distributions will then exist for each operator. The feedback onboard can then be compared to all operators for that machine or to the currently logged on operator.

An overview of the Database Structure is described below.

TABLE 2 – KPI Configuration Information

Contents
KPI Parameter ID
Text description of KPI
Maximum number of Mixtures in a segment
Left / Right distribution
Length of moving average filter

The KPI Configuration information describes the global settings used in the system as shown in TABLE 2. The KPI Parameter ID identifies the parameter used in the calculation of the distributions and the comparisons. The text description is used to display the KPI name on the Reports/Forms. The maximum number of mixtures is set here when using the LBG method. The maximum is likely to be 4, but this will probably vary depending on the KPI. The number of mixtures that are actually used can be smaller than this number. The Left or right distribution value determines how to calculate the KPI onboard the machine. As discussed above with reference to FIG 5, if it is a left distribution, then it means that a higher KPI variable is required to obtain better performance, e.g. Return Time. A right distribution means that a lower KPI is required to obtain better performance, e.g. Swing Production. A moving average filter can be optionally applied to the KPI result.

TABLE 3 Segment Information

Contents
The ID of this segment
KPI Parameter ID
ID of the machine
ID of the dig mode
ID of the bucket
ID of the operator

The Segment Information contains all the combinations of machines, dig modes, buckets, and operators in the mine for each KPI and associated segments as shown in TABLE 3. The KPI Distribution Calculation routine inserts all the entries into this table after it has determined the segmentation of the data. The segment ID identifies the segment for the current KPI, machine, dig mode, and the like.

TABLE 4 Segmentation Offset Information

Contents
ID of the machine
ID from Parameter Link Information
Offset of the segment (cm, degrees, etc.)

The Segmentation Offset Information contains the offset values for dependent parameters associated with a KPI as shown in TABLE 4. These need to be configured for each machine for which KPI distribution calculations will be performed.

TABLE 5 Dependency Information

Contents
The ID of this segment
The ID of the dependent parameter
Lower limit of dependent parameter
Higher limit of dependent parameter

The Dependency Information contains the high and low limits for each

dependent parameter within each segment and is calculated by the KPI Distribution Calculation routine.

TABLE 6 Distribution Information for the LBG method

Contents
The ID of this segment
Mixture weight of the distribution
Mean of the distribution
Standard Deviation of the distribution

The Distribution Information contains the distribution models for each of the segments. The information stored here depends on the distribution calculation method that is employed.

For the LBG method, TABLE 6 shows the information that is used. For each segment the mixture weight, mean and standard deviation are stored for each mixture within the segment.

TABLE 7 Distribution Information for the LRM method.

Contents
The ID of this segment
Maximum distribution value
Minimum distribution value

For the LRM method, TABLE 7 shows the information that is used. For each segment the maximum and minimum distribution values are stored.

TABLE 8 Parameter Link Information

Contents
KPI Parameter ID
The ID of a parameter
Specifies whether or not the parameter is dependent

The Parameter Link information shown in TABLE 8 is used to allow parameters to be associated with a KPI. Values for associated parameters

that are not dependent will be added to values for the KPI. Other parameters are dependent parameters.

TABLE 9 Parameter Information

Contents
The ID of a parameter
Text description of the parameter

The Parameter Information shown in TABLE 9 is used to identify the KPI Parameter ID with which the parameter is associated. This is used to identify which KPI parameter and dependent parameters are used in the modeling.

The KPI Distribution Calculation routine is an NT service that is scheduled to run on a periodic basis.

The program collects the data, segments it and calculates the distributions for each segment and stores the results in the kpi_distribution table. While this program is running, the system (mainly Telemetry) knows not to acquire any of the data from any of the KPI tables. This is because this program may take an order of hours to calculate all the data. It may be necessary to set the priority of this task to low in the system in case the processing time is significant.

The requirements for Telemetry are simple and would generally be familiar to a person skilled in the art. The onboard module, as shown in FIG 6, needs to request the KPI parameters that are currently in the database, but only if they have been changed. The onboard unit will request the data, for example, every 8 hours. If the KPI Distribution Calculation routine is running then Telemetry needs to instruct the onboard unit to defer the request until later. It does this by setting the KPI timestamp in the reply packet to zero.

The timestamp when the data was last changed is recorded in a table in the database. The onboard module will send an initial KPI request packet as described later herein. Telemetry replies with the basic KPI configuration data and the timestamp of when the service last ran. If the service is running

the timestamp is set to zero. The timestamp is also sent with every packet during the download so that if the service starts while downloading, the onboard module can detect that the timestamp has gone to zero and it can abort the download.

The Telemetry Packet Structures will now be described.

The onboard module sends a KPI Configuration Request packet to Telemetry to request the KPI configuration. Telemetry replies with a KPI Configuration packet, for which the contents are shown in Table 10. It places the timestamp in which the KPI Distribution Calculation Routine last ran into this packet. The onboard module then compares this timestamp with the one it has to see if it needs to start downloading the KPI segments.

TABLE 10 - KPI Configuration Packet

Contents
The timestamp of when the data was last updated.
Number of KPIs in the database
The index of the KPI that we are replying to.
KPI Parameter ID
Number of taps in the Moving average filter to apply to KPI output.
The good to excellent threshold score (%)
The poor to good threshold score (%)

A KPI Segment Request packet, as shown below in Table 11, requests the data (distributions and the like) from Telemetry. The reason for including the Dig Mode ID, bucket ID and the operator ID in the packet is to enable prioritization of the download of the KPI distributions if required.

The first packet contains a segment_index of 1 to request the first segment and subsequent packets contain the next segment that the system wants. The requests stop when all the segments for that machine have been downloaded.

TABLE 11 - KPI Segment Request packet

Description
KPI Parameter ID
Index to the segment for this KPI.
The current dig mode entered on the machine.
The current bucket on the machine.
The currently logged on operator.

A KPI Segment packet shown in Table 12 below is the reply to the KPI segment request packet. If there is no distribution for the segment, then the Distribution information contains nothing.

TABLE 12 - KPI Segment packet

Contents
The timestamp of when the data was last updated.
The Total number of segments for this KPI (including ALL dig modes and ALL buckets and ALL operators).
KPI Parameter ID
Dig mode ID of this distribution
Bucket ID for this distribution
Operator ID for this distribution
The Segment ID
Distribution Information
The Production contribution of this segment.
Number of dependent parameters in this segment
First dependent parameter ID
Lower limit of the dependent parameter
Higher limit of the dependent parameter

The Series 3 Computer Module shown in FIG 6 needs to download the KPI configuration and distribution information. It stores this onboard in Flash memory. Once this information is downloaded, it is responsible for calculating the KPI scores after every cycle as previously described herein. If the LBG algorithm method described above is being used, a Gaussian lookup table may be used to calculate the Gaussian curve instead of using the Gaussian distribution equation specified above.

In order for the Series 3 Computer Module to calculate the score, it

firstly selects the distribution by determining the segment that the current cycle matches for the particular KPI. Once the distribution has been found, then the KPI score can be calculated. If there exists no distribution to calculate a KPI, then the KPI score will be 100% (or 10 if the LRM is being used).

The scores for all the KPIs are calculated for both the mine and current operator comparison. Therefore, there are 2 scores that need to be calculated for every KPI.

The KPI can be displayed as a real-time parameter in the parameter list on a STATS screen. It may also be displayed as a trend so that the operator can see any performance improvements. The trend may be configured by the operator to show the graph for the last hour or the current shift or other suitable period. This is performed using the KPI trend configuration that is displayed once the operator selects one of the trend graphs from a menu displayed on the STATS screen.

A third option is to display a KPI indicator that is again selected in the trend configuration. Three different designs for the indicator are shown in FIGS 7-9 The KPI indicator could appear white against a black background to enhance visibility. FIG 7 shows the current real-time performance. The arrows above each KPI indicate whether or not the score has improved from the last cycle. The extent to which the KPI has improved or deteriorated may also be shown. FIG 8 shows an alternative method of displaying the real-time KPI scores for each of the KPI variables including an overall performance rating, which may be the average of the KPI variables. FIG 9 shows an alternative way of displaying the scores for the previous cycle so that the operator can judge any improvements or deteriorations from cycle to cycle. This version could include more than just the last cycle.

The IMS Application preferably supports editing of some of the KPI Parameters. The following parameters need to be available to an IMS administrator for editing: KPI text description; the setting of the good and average thresholds for the KPI indicator; frequency of running the KPI

Distribution Calculation routine (KPI Statistical Generator); number of days of previous data to be used to create the models; display of the last time the KPI data was updated and the like.

Reports, such as an Operator Performance Trend Report and an Operator Ranking Report, as shown in FIG 10 and FIG 11 respectively, may also be generated from the Report Manager in the IMS Application.

The Operator Performance Trend report shows the graphical trend of an operator for each of the selected KPI variables. The options that should be made to the person generating this report should include: Sort by machine, Sort by dig mode, Sort by bucket, Set Time period, Number of operators to show (top, specified number or all) and The KPIs to show.

The Operator Performance Trend report needs to calculate the KPI values over the selected time period based on the distributions contained in the Database at the time. Therefore, the KPI scores need to be calculated again. The reason for this is that the scores that were shown to the operator onboard are no longer valid because the distributions would have changed during that time and therefore cannot be compared to each other. Because the Report Manager has to do these calculations, the report may take a long time. Therefore, the time period over which the trends are calculated will have to be limited.

The Operator Ranking report displays the ranking of operators for each of the KPIs. That is, for a particular KPI or all KPIs, it displays the ranking of all the operators. The time period needs to be selected and, as for the previous report, this time period will have to be limited as the report may take a long time to run. This report needs to calculate what the previous report calculated, but needs to average the output scores.

The options that should be made to the person generating this report should include: Sort by machine, Sort by dig mode, Set Time period, Number of operators to show (top, specified number or all), The KPIs to show.

An Average Production KPI may be provided that is calculated remotely and downloaded to the Series 3 module in the machine. This may

be displayed on the performance graphs to show the operator their current performance relative to their average. This value can be downloaded along with the operator ID lists.

Current practice used by all mines estimating operator performance on the basis of Productivity appears to be wrong. Under different conditions and production plans some of the operators could be disadvantaged against others. For example, if an operator works in the same conditions, but with different swing angles from another operator, productivity shown for the greater swing angle will be less than for smaller swing angle, even though the first operator may in reality be more efficient.

Taking into account that the number of effecting factors could include a number of other parameters, the applicant has identified that in order to be able to compare productivity ranks of the same operator under different conditions, some integrated value that could be used for ranking purposes should be used.

In order to be able to calculate average rank for operators working under different conditions, integrating performance ranks achieved under different conditions by different operators should be considered on the one hand and mine interests and production performance should be considered on another hand.

The suggested method of the present invention in this regard will include these 2 parameters as variables and will allow calculation of average operator rank, which could be used as a universal rank among the mine for different machines, conditions and production plans.

The formula for calculation of average operator rank is presented below:

$$\text{Av Op Rank} = W_1 * R_1 + W_2 * R_2 + ... + W_I * R_I$$

Where:

W_i – Weight coefficient for Parameter Subset I, which is calculated on the basis of statistical information for the mine indicating the weight of i Parameter subset for the mine applicable to operator i

R_i – Rank of the operator i achieved for this Parameter Subset i.

For example, let it be assumed that during a reporting period a mine used only 4 different subsets of parameters. The weight of each subset could respectively be the following: 25%, 20%, 40% and15%. If operator #1 worked only under subset #1 and # 2 and achieved 90% for subset # 1 and 94% for subset #2, using the above formula the average rank for the operator may be calculated:

$$\text{Av Op Rank} = \frac{25}{45}x90\% + \frac{20}{45}x94\% = 91.8\%$$

For Operator # 2 subset #3 = 92% and subset # 4 = 90%:

$$\text{Av Op Rank} = \frac{40}{55}x92\% + \frac{15}{55}x90\% = 91.45\%$$

These Productivity ranks do not include Production figures and only rank operators for different subsets of parameters. In reality, if, for example, operator 1 was doing cycles with swings of say 10 and 20 degrees and operator 2 170 and 180 degrees, then the real production for operator 1 could be twice as much as for operator # 2, but in fact rank of operator # 1 is higher and accordingly he is better.

It is also conceivable that the average performance of an operator over the last week or month could be shown. The average performance could be calculated remotely and the onboard module would download it to the machine for every operator. It would be treated just as a list download where one radio packet represents one graph. Only the minimum and maximum values need to be sent and then each of the data points can be percentage scaled.

Accurately determining one or more of the KPIs in accordance with the present invention addresses the difficulties of accurately measuring relevant parameters and producing fair comparisons. The present invention can be used to improve awareness of how well the operators are performing and provide an incentive to improve performance. It also provides an indication to management about who is performing well and which operators are not performing up to standard.

Throughout the specification the aim has been to describe the invention without limiting the invention to any one embodiment or specific collection of features. Persons skilled in the relevant art may realize variations from the specific embodiments that will nonetheless fall within the scope of the invention.

Dated this Twenty-Fifth day of January 2002

TRITRONICS (AUSTRALIA) PTY LTD

By their Patent Attorneys

FISHER ADAMS KELLY

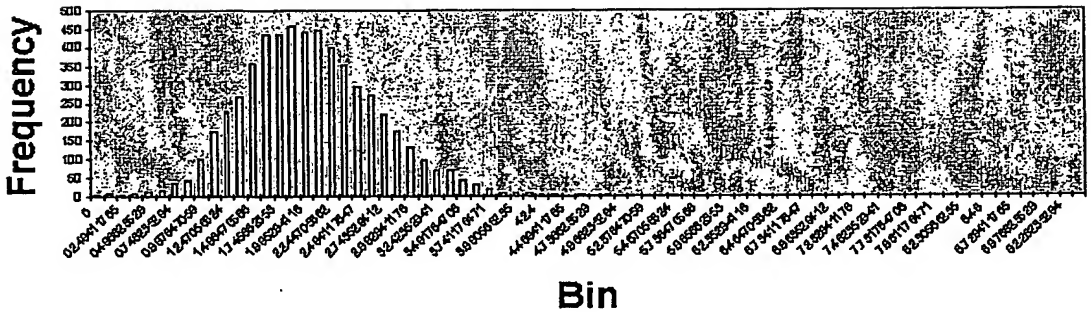


FIG 1

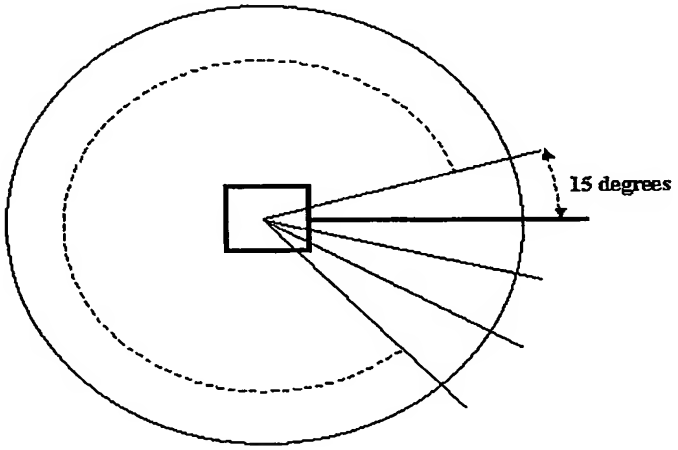


FIG 2

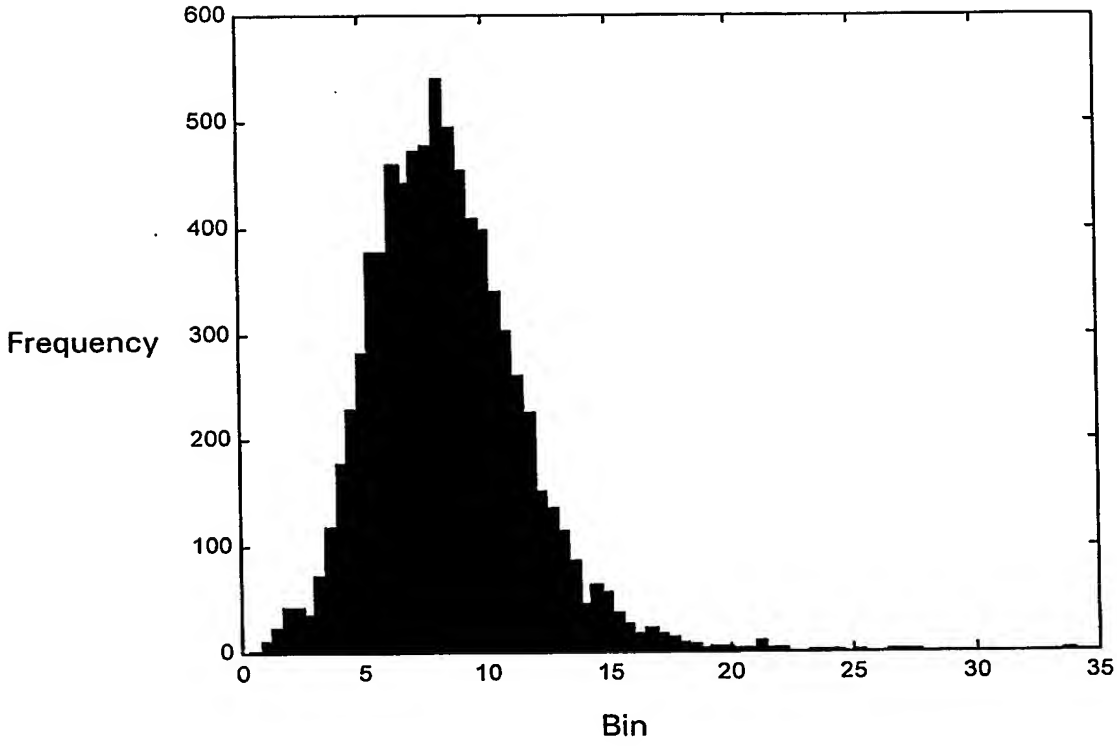
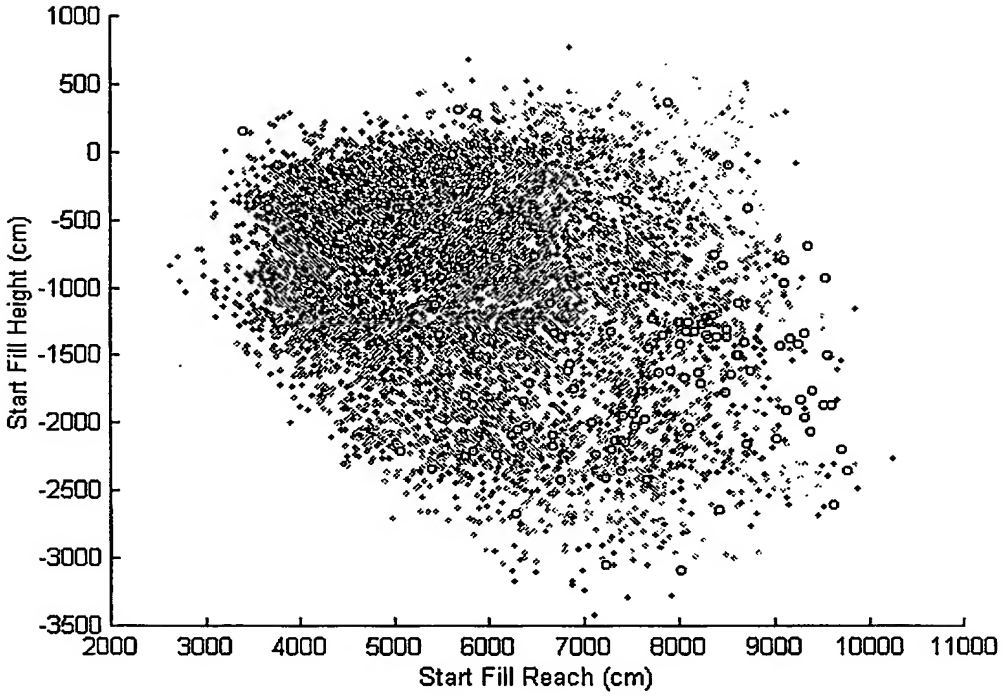


FIG 3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-500
-1000
-1500
-2000
-2500
-3000
-3500
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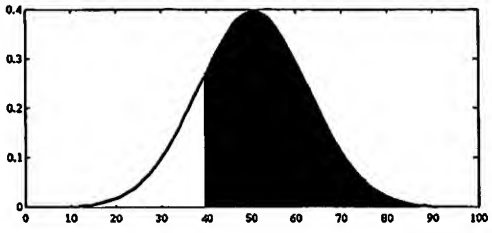
3000
4000
5000
6000
7000
8000
9000
10000
11000
Start Fill Reach (cm)

FIG 4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0.1
0
0
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60
70
80
90
100

FIG 5

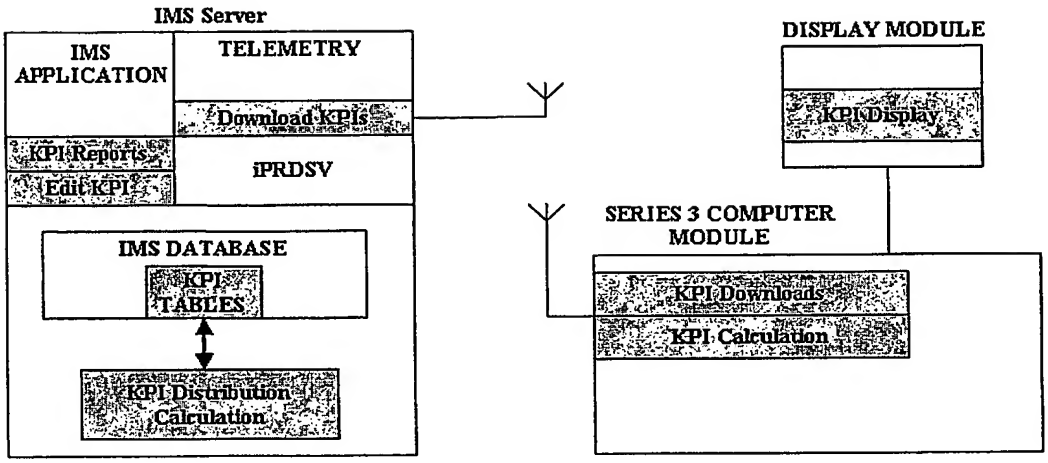

IMS Server
IMS APPLICATION
TELEMETRY
Download KPIs
KPI Reports
Edit KPI
iPRDSV
IMS DATABASE
KPI TABLES
KPI Distribution Calculation
DISPLAY MODULE
KPI Display
SERIES 3 COMPUTER MODULE
KPI Downloads
KPI Calculation

FIG 6

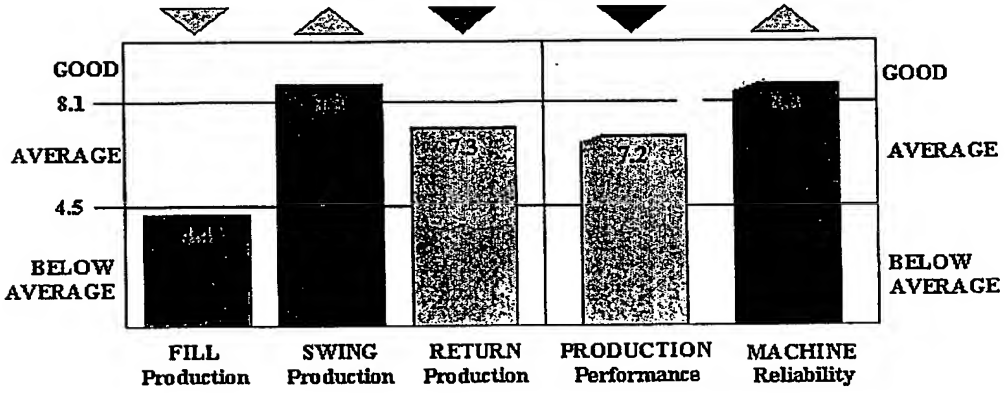

GOOD
8.1
AVERAGE
4.5
BELOW AVERAGE
GOOD
AVERAGE
BELOW AVERAGE
7.3
7.2
FILL Production
SWING Production
RETURN Production
PRODUCTION Performance
MACHINE Reliability

FIG 7

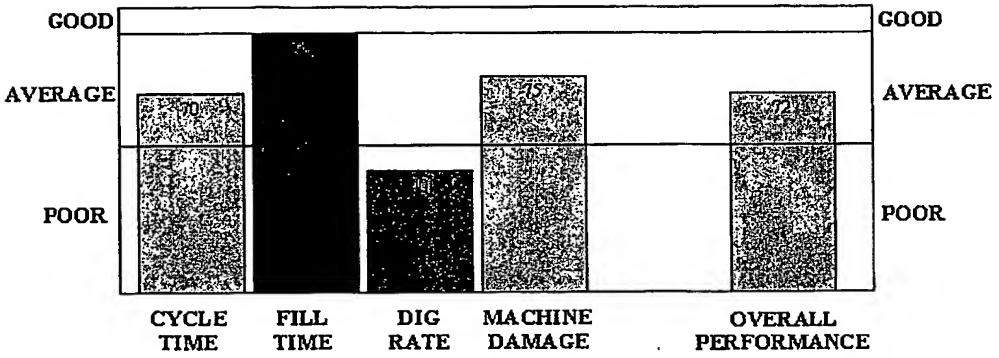

GOOD
AVERAGE
POOR
GOOD
AVERAGE
POOR
70
75
72
CYCLE TIME
FILL TIME
DIG RATE
MACHINE DAMAGE
OVERALL PERFORMANCE

FIG 8

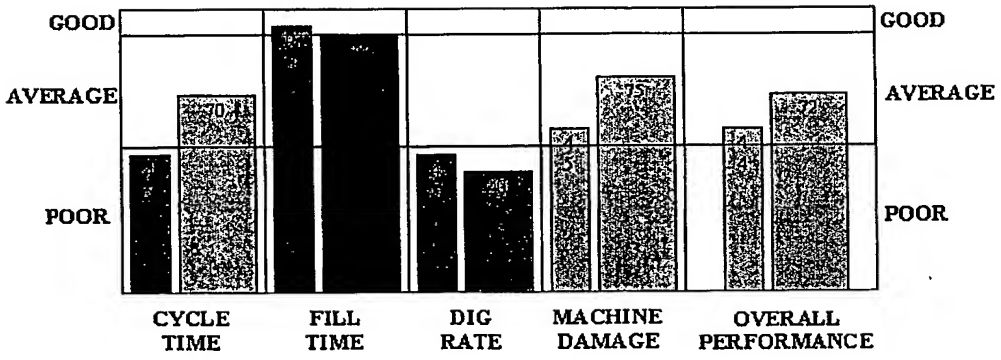

GOOD
AVERAGE
POOR
GOOD
AVERAGE
POOR
70
75
72
CYCLE TIME
FILL TIME
DIG RATE
MACHINE DAMAGE
OVERALL PERFORMANCE

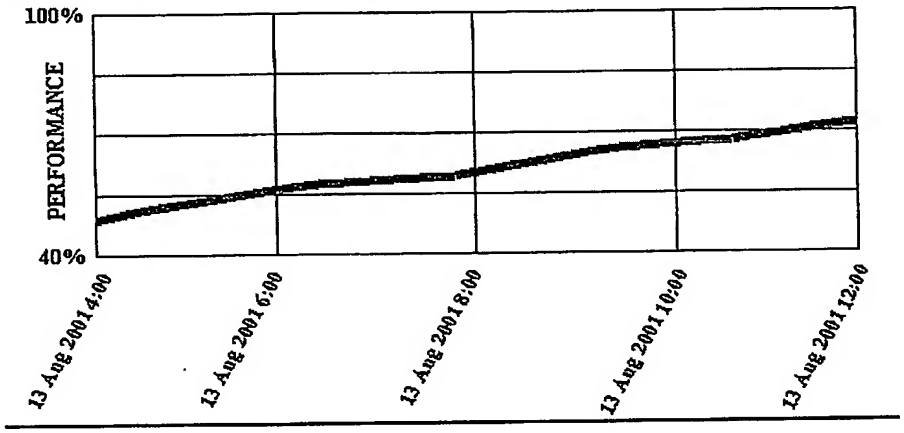
FIG 9

OPERATOR PERFORMANCE TREND REPORT

Time Period: 13 Aug 2001-14 Aug 2001
Machines: All machines
Dig Mode: All Dig Modes

OPERATOR: Joe Bloggs

Fill Time **Minimum: 43% Maximum: 72% Average: 65%**



OVERALL **Minimum: 43% Maximum: 72% Average: 65%**

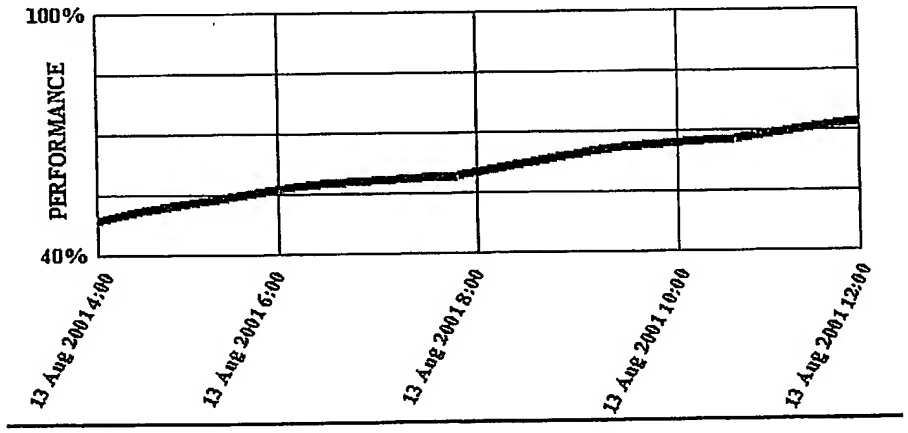


FIG 10

OPERATOR RANKING REPORT 2001 **Time Period: 13 Aug 2001-14 Aug 2001**

Machines: All machines
Dig Mode: All Dig Modes

Fill Time

Ranking	Operator	Average Score	Machine
1	Joe Bloggs	68%	DRE15
2	Harry Smith	66%	DRE8
3	John Smith	58%	DRE15

Swing Time

Ranking	Operator	Average Score	Machine
1	John Smith	90%	DRE15
2	Joe Bloggs	85%	DRE15
3	Harry Smith	82%	DRE8

OVERALL

Ranking	Operator	Average Score	Machine
1	John Smith	90%	DRE15
2	Joe Bloggs	85%	DRE15
3	Harry Smith	82%	DRE8

FIG 11

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